Financialization of Agricultural Commodity Markets:
Do Financial Data Help to Forecast Agricultural Prices?

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Abstract

The dramatic rise in commodity index investment have made many market analysts and researchers believe that commodity markets have undergone a financialization process that forged a closer link between commodity and financial markets. I empirically test whether this hypothesis is true in a forecasting context by using high-frequency financial data to forecast monthly US corn prices. Specific financial series examined include the Baltic Dry Index, the US exchange rate, the Standard and Poor's 500 market index, the 3-month US Treasury bill interest rate, and crude oil futures prices. Using a recently developed statistical model that deals with mixed-frequency data, I find that while some improvements may be made when including high-frequency financial data in the forecasting model, the improvements in mean-squared prediction error and directional accuracy using such models are minimal, and that models generated from random walk and autoregressive models perform satisfactory well compared to more complicated models.

Keywords: mixed-frequency data, corn prices, volatility, price forecasting, mean-squared prediction error, directional accuracy, commodity index funds, financial market, financialization

JEL codes: Q11, Q14, O13, C5, C00

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1. Introduction

Agricultural commodity prices have undergone large fluctuations since 2006, often characterized by extreme upward and downward movements. Corn prices, for example, nearly tripled between 2000 and 2008, rising from less than two dollars per bushel to almost six dollars per bushel in nominal terms. After plummeting dramatically from its mid-2008 peak, the price of corn skyrocketed again in 2011, pushing beyond seven dollars per bushel in August 2012. Many other agricultural commodities experienced a pricing rollercoaster during this period as well. The resulting food price volatility has led to economic hardship among the poor and irreversible damages from nutritional deficiencies among children in developing countries (World Bank 2008), and may have been responsible for political turmoil in many countries (Bellemare 2014). The extensive and negative consequences associated with the recent episode of food price fluctuations highlight the critical importance of understanding the causes behind this heightened price volatility.

A common contributing factor of extreme agricultural commodity prices cited by numerous market analysts and academic researchers is speculation in futures markets. Precipitated by a few influential academic studies which conclude that investors can capture substantial risk premiums and reduce portfolio risks by investing in long-only commodity index funds (e.g., Erb and Harvey 2006, Gorton and Rouwenhorst 2006), a substantial amount of money was moved into commodity futures markets in the form of commodity index investment by institutional investors (e.g., pension funds) and wealthy individuals.. Irwin and Sanders (2011) estimates that between 2004 and 2008, at least $100 billion of new investments were moved into commodity futures markets.

Since investors often strategically allocate their portfolios among a basket of assets, they often invest in a variety of financial assets in addition to commodity index funds. It is thus highly possible that the increasing presence of index investors in commodity markets have forged a closer link between commodity and financial markets. Domanski and Heath (2007) were the first to label this process the "financialization" of commodity futures markets. Tang and Xiong (2012) find that not only price comovements between different commodities have increased after 2004, but also the correlation between commodities and the Morgan Stanley emerging market equity index has increased. They further argue that as a result of financialization, commodity prices are now jointly determined by a whole set of financial factors in addition to its own supply and demand conditions, and volatility in financial markets can spill over to commodity markets.

A heated public debate ensued in 2008 regarding the role of index investment and the impact of commodity markets financialization. Masters (2008, 2009) argue that the unprecedented buying pressure from financial index traders created a series of massive bubbles in agricultural futures prices, which was further transmitted to the spot market through the normal arbitrage relationship, eventually leading to skyrocketing commodity prices. The key idea behind this argument is that the long-only investment activities carried out by commodity index traders (CITs) are essentially synthetic long positions in physical markets that affects commodity prices though futures markets if they exceed the underlying supplies. This argument is often termed as the "Masters' hypothesis" in the literature (e.g., Irwin and Sanders 2012). Similar concerns on CIT activities were expressed by the U.S. Senate Permanent Subcommittee on Investigations in its examination of the performance of the CBOT wheat futures contracts, that "….these commodity index traders, in the aggregate, were one of the major causes of 'unwarranted changes'—here, increases – in the price of wheat futures contracts relative to the price of wheat in the cash market" (USS/PSI 2009).

Existing studies testing for the existence of commodity markets financialization have largely followed three paths. The first uses Granger-type analyses to test whether changes of CIT positions help to forecast commodity price movements, with the majority concluding that little causality may be identified from CIT position changes to commodity price returns (e.g., Stoll and Whaley 2010, Sanders and Irwin 2011, Etienne, Irwin and Garcia 2012, Lehecka 2013, Hamilton and Wu 2014). Unlike the Granger-type studies that typically ignore the underlying commodity market structure, the second type of studies attempt to use a structural or reduced-form model to estimate the impact of speculation on commodity price behavior (e.g., McPhail, Du and Muhammad 2012, Bruno, Büyükşahin and Robe 2013, Carter, Rausser and Smith 2013, Janzen, Smith and Carter 2013, Baumeister and Kilian 2014). These studies also conclude that speculation or commodity market financialization is unlikely to cause commodity prices to significantly depart from fundamental values. The third path of research attempts to empirically test for the existence of bubbles in commodity markets using newly-developed time series procedures (e.g., Gilbert 2010b, Areal, Balcombe and Rapsomanikis 2013, Gutierrez 2013, Etienne, Irwin and Garcia 2014a, b). Overall, these papers conclude that while bubbles do exist, they only constitute a very small portion of the price behavior.

In this paper, I apply a very different approach than past studies. Specifically, I argue that if the financialization of commodity markets have indeed affected commodity markets and have further impacted the behavior of commodity prices, then information in the financial market should help to forecast commodity price movements. In particular, given that financial information is usually publically available at a higher-frequency than agricultural commodity data, forecasts that incorporate high-frequency financial data are likely to be superior to those that do not. For this reason, I use the Mixed-data sampling (MIDAS) regression approach of Ghysels, Santa-Clara and Valkanov (2004, 2006) that incorporates daily financial data to generate monthly corn price forecasts. Then to assess the MIDAS forecast performance, I generate two benchmark forecasts, one based on the assumption that commodity prices behave like a random walk—the no-change forecast—and another based on an autoregressive model.

The purpose of this paper is twofold. First, given (1) the arrival of new market participants that often invest in the financial market as well and (2) the notion that agricultural commodity prices are increasingly correlated with the financial market, we aim to examine whether higher-frequency information in the financial market contains some predictive component of future price movements in the corn market. If the financialization of commodity markets indeed cause commodity prices to move together or at least be more linked to financial indicators, financial information available at a higher frequency are likely to help forecast commodity prices and improve the forecast performances of statistical models. On the other hand, if little improvement in forecasting performances is made when using higher-frequency financial data, commodity markets may not have been as "financialized" as many people have argued, or at least not integrated with the financial market in the perspective of information flow. Additionally, we also examine the performance of various forecasting models over a long sample period. With the financialization of commodity markets that occurred around 2006, one would expect financial information to help forecast commodity prices after 2006 but not prior.

Second, given the recent large volatility in agricultural commodity prices, a renewed interest in academic research is to improve the performance of forecast models and generate more accurate price forecasts. This is not only of particular importance for producers and industry raw-material users who wish to manage their price risks, but also for developing countries with export revenues largely dependent on agricultural commodities that wish to better manage their national financial accounts. This is an incredibly important question, as the rising uncertainty in commodity prices can have both short-term and long-lasting negative impacts on economic development. It is therefore imperative to generate forecasting models that can better predict future price movements, so that economic activity may be planned accordingly.

The remainder of the paper proceeds as follows. In the next section, I discuss various forecasting models that can be used to test for the predictive content of high-frequency financial data on monthly corn prices in the US. The focus is on the MIDAS model introduced by Ghysels, Santa-Clara and Valkanov (2004, 2006). Alternative forecasting models that do not use exogenous financial information are also discussed. These models are used as a benchmark to measure the performance of the MIDAS model. In section three, I describe the data used in the analysis and discuss relevant issues of data construction. Specific high-frequency financial data used include the Baltic Dry Index (BDI), US dollar exchange rate, interest rate, crude oil prices, and S&P 500 index, all with daily frequency. Section three discuss the forecast evaluation methods. Section five provides results, and the last section concludes the paper.

Overall, I find that while some improvements may be made using high-frequency financial data to forecast corn prices, the improvements in mean squared prediction error (MSPE) and directional accuracy are minimal. In fact, benchmark forecasts that do not use high-frequency data and are only dependent on their own past values often perform no worse or better than models using high-frequency financial data. In other words, it remains hard to beat the forecasts generated from a random walk or autoregressive model, even during a period when agricultural commodity prices are increasingly correlated with the financial market. While the financialization of commodity markets brought by index traders in agricultural futures markets may improve the responsiveness of agricultural prices to various financial factors, clearly the high-frequency information embedded in financial markets has not been fully incorporated in agricultural prices, at least from a forecasting perspective.

2. Forecasting Models

Consider, for instance, the case of forecasting h- period ahead monthly prices using a single explanatory variable X that is sampled at the daily frequency. One traditional approach to deal with such a data imbalance is to aggregate the daily data to the monthly frequency, as in equation (1):

$$P_{t+h}^{M} = \alpha + \sum_{i=1}^{I} \rho_i L^i P_t^M + \beta X_t^M + \varepsilon_{t+h}, \text{ and}$$

(1)

$$X_t^M = \frac{1}{K} \sum_{k=1}^{K} L^k X_t^D,$$

where the current period price P_t^M is sampled at the monthly frequency (M), L is the lag operator such that $L^i P_t^M = P_{t-i}^M$, $i = 1, \ldots. I$ are the orders of autoregressive lags, X_t^M is the monthly average of daily data X_t^D (sampled at a daily frequency, D) at month t, ε_{t+h} is the error term at period $t + h$, and α, β, and ρ are parameters to be estimated. The autoregressive lags are included to account for serial autocorrelation that commonly exists in monthly prices. Equation (1) is equivalent to estimating an autoregressive exogenous (ARX) model that uses aggregated monthly data of the independent variable. While the ARX model is easy to implement, the main drawback with this type of model is that information contained in the high-frequency data is dismissed and the average monthly price cannot capture the variations embedded in daily observations. As a result, using (1) to forecast prices may incur misspecification bias. The forecasts generated by ARX model may be written as:

(2) $\hat{P}^M_{t+h} = \alpha + \sum_{i=1}^{I} \rho_i L^i P^M_t + \beta X^M_t.$

To remedy this, a second common practice in the literature uses all daily observations to forecast monthly prices, as in (2):

(3) $\hat{P}^M_{t+h} = \alpha + \sum_{i=1}^{I} \rho_i L^i P^M_t + \sum_{k=1}^{K} \beta_k L^k X^D_t.$

Here, the lag operator $L^k X^D_t = X^D_{t-k/K}$ such that it represents the daily observation at period $t - k/K$ (days) that is within month $t-1$ and month t. As can be seen, while model (2) uses all the information embedded in the daily data, the number of parameters needs to be estimated is $I + K + 1$, which can become rather large when the frequency of the independent variable X becomes high relative to the frequency of P. Though estimating a large number of parameters as in (2) will reduce bias, it may suffer from the problem of large forecast variance when the sample size is small.

2.1. MIDAS Model

The MIDAS model of Ghysels, Santa-Clara and Valkanov (2004, 2006) is a parsimonious way of using high-frequency regressors to forecast a lower-frequency right-hand-side variable. As can be seen in equation (4), the basic structure of the ADL-MIDAS model that includes autoregressive lags is rather similar to (3):

(4) $P^M_{t+h} = \alpha + \sum_{i=1}^{I} \rho_i L^i P^M_t + \beta \sum_{k=1}^{K} B(k; \boldsymbol{\theta}) L^k X^D_t + \varepsilon_{t+h},$

where the function $B(k; \theta)$ is a polynomial that determines the weights for temporal aggregation of the daily observations X^D_t. As noted by Ghysels, Santa-Clara and Valkanov (2006), the parameterizing of the weighting function $B(k; \theta)$ in a parsimonious way is one of the key features of the MIDAS model. Various approaches to parameterize $B(k; \theta)$ is available, including normalized Beta probability density functions, unrestricted polynomials, step functions, etc. Ghysels, Sinko and Valkanov (2007) provides a detailed discussion on this issue. In this paper, I follow Ghysels, Santa-Clara and Valkanov (2004) and use an exponential Almon specification of the weighting function, as in (5):

$$B(j;\theta_1,\theta_2\,) = \frac{\exp(\theta_1 j + \theta_2 j^2)}{\sum_{k=1}^{K}\exp(\theta_1 j + \theta_2 j^2)} \tag{5}$$

As it appears, when $\theta_1 = \theta_2 = 0$, the ADL-MIDAS model in equation (4) imposes equal weight on temporal aggregation when using exponential Almon specification, and is thus equivalent to the ARX model as in (1). Such model may be referred to as the equal-weighted MIDAS model. In this case, the only parameters needs to be estimated are β, α, and the autoregressive coefficients ρs. The equal-weighted MIDAS framework may be appealing in small samples when the classical bias-variance tradeoff is a concern in forecasting (Baumeister, Guérin and Kilian 2014). As a general form, the forecasts generated by MIDAS model may be written as:

$$\hat{P}_{t+h}^{M} = \alpha + \sum_{i=1}^{I} \rho_i L^i P_t^M + \beta \sum_{k=1}^{K} B(k;\boldsymbol{\theta}) L^k X_t^D. \tag{6}$$

2.2. Alternative Forecasting Models

A natural benchmark for forecasts based on MIDAS models is the no-change forecast. The efficient market hypothesis contends that price changes are unpredictable, and prices should behave as a random walk (e.g., Fama 1970). Alquist and Kilian (2010) find that the no-change forecast of monthly spot oil prices generated from a random walk model without drift (or simply the last period price) outperforms oil futures-based forecasts in the sense of mean-squared prediction error. They argue that the inferiority of futures-based forecasts is due to the variability of the futures price about the spot price captured by the oil futures spread. The no-change forecast is defined as in (7). Of course, the performance of no-change forecast deteriorates as the forecasts horizon increases, due to lack of recent information input into the forecast.

$$(7) \qquad \hat{P}^{M}_{t+h} = P^{M}_{t}.$$

Another alternative forecast that does not depend on exogenous information is the price forecast generated from an Autoregressive integrated moving average (ARIMA) model. For simplicity, forecasts made from an AR(I) model are generated, which may be written as in (8):

$$(8) \qquad \hat{P}^{M}_{t+h} = \alpha + \sum_{i=1}^{I} \rho_i L^i P^{M}_{t}$$

3. Data

Every month, the US National Agricultural Statistics Service (NASS) publishes the monthly average prices of corn received by farmers in the US. This price is obtained through a survey of approximately 2,000 mills, elevators, and buyers monthly in the top producing states. Data on total dollars received by farmers and the total quantity purchased from farmers are collected, and the price received by farmers is calculated as the ratio of these two quantities. While the price received by farmers may be different from actual market prices, this price data has been widely used in short and long-term government planning, including agricultural production valuation, insurance programs, counter-cyclical and disaster payments, etc. This price data have also been used extensively in the academic literature to forecast seasonal average prices in the US. In this paper, the monthly prices received by farmers are used as a proxy for cash prices. I attempt to assess whether higher-frequency financial data provide predictive component of monthly corn prices in the US, and if they do, how their predictabilities have changed over time as index traders enter the markets.

I consider the following five individual high frequency data series: (1) the Baltic Dry Index (BDI) from Bloomberg; (2) 3-month Treasury bill interest rate from the US Federal Reserve Bank; (3) the Standard and Poor's (S&P) 500 stock index from Yahoo! Finance; (4) the nominal trade-weighted U.S. dollar index in terms of major currencies from the Federal Reserve Bank; and (5) nearby WTI crude oil futures prices from the New York Mercantile Exchange (NYMEX). All these data are available at a daily frequency, and reflect rather different aspects of the financial markets. Table 1 provides the details of each data series. As can be seen, the availability of data varies by variables. Since the price of corn is not available until January 1960, we trim the S&P 500 Index and interest rate data to start from January 1960 as well.

One practical problem inherent to daily data is that different months contain different numbers of daily observations. Not only is the number of days per month different (28-31 days), but daily observations may also be missing due to weekends, holidays, special events, etc. The number of actual daily observations available each month for data used in this study in fact ranges from 15 to 26. Since MIDAS can only deal with data consisting of a constant number of observations, this unbalanced data problem clearly needs to be addressed before proceeding to the forecasting analysis. Previous literature dealing with daily data usually takes one of the two approaches: use linear interpolation to obtain missing data or cut the number of observations to the minimum available number of observations for each month. For instance, Breitung, Roling and Elengikal (2013) uses linear interpolation to fill in the missing observations in each month to obtain a constant number of daily observations. By contrast, Andreou, Ghysels and Kourtellos (2013) fix the number of observations in a month to be 22 when predicting macroeconomic forecasters using daily financial data. Similarly, Hamilton (2008) uses 21 business days in a month when investigating the effects of daily monetary policy shocks on new home sales. Here, I use a mixture of these two approaches, i.e. first setting the number of daily observations included in each month to 20, then linearly interpolating missing values when less than 20 observations are available within a month. Since the minimum number of daily observations within a month is rather small (15), fixing the daily observations to that number would significantly reduce daily variations for months in which more daily data exist. Using the maximum number of observations within a month, or 26 days, on the other hand, would induce bias in some months, particularly when more than 40 percent of the data are missing.[1]

Figure 1 plots the monthly average prices of corn received by farmers in the US since January 1960. I consider forecasting the nominal prices for two reasons. First, at any point of time, producers, consumers, and other market participants would be mostly interested in nominal prices in the future rather than real prices. In particular, given that the forecasting horizon in this paper is rather short (less than one year), the CPI deflator is unlikely to significantly vary in a short time period. Second, to forecast real prices, one would need to forecast the value of CPI, which may introduce additional uncertainty and bias into the forecasting model. As can be seen, corn prices have been rather volatile during the sample period, with peaks observed in the mid-1970s, again in the mid-1980s and late-1980s, then in the mid-1990s, and finally in the late-2000s and early-2010s. In addition, large run-ups in prices are often followed by dramatic drops in corn prices. The volatile behavior of corn prices calls for a careful evaluation of the forecasting performance of various models, as well as an identification of the role of commodity market financialization.

[1] For instance, to obtain 26 daily observations when only 15 observations are available in a month, we would need to use linear interpolation to fill in 11 missing observations. This constitutes 42% of the total data in this month.

Figure 2 plots the daily values of the exogenous variables used in the analysis. As can be seen, with the exception of the BDI index and crude oil prices, the behavior of the remaining three variables differs substantially. For instance, while the S&P 500 in general increases during the sample period, the US exchange rate against other major currencies mostly decreases. The 3-month Treasury bill rate peaks in the beginning of 1980s (close to 20%), but has dropped close to 0% since January 2010. Both BDI index and crude oil prices peaked in late-2000s, with dramatic downward movements observed in the end of 2008. However, unlike crude oil prices which have risen again since the beginning of 2010, the BDI index has maintained a relatively low level. It is interesting to examine whether the rich information included in the high-frequency data provide additional forecast power to corn prices.

4. Forecast Evaluation Methods

I calculate two indicators to evaluate the performance of various forecasting models discussed in this paper. The first indicator is the mean-squared prediction error, or MSPE, as defined in (9):

$$MSPE = \frac{1}{N}\sum_{i=1}^{N}(P_t^M - \hat{P}_t^M)^2, \quad (9)$$

where P_t^M and $\hat{P}_t^M$ are the actual and forecasted prices at month t, respectively. M indicates a month frequency. The term $(P_t^M - \hat{P}_t^M)$ is often referred to as the forecast (or prediction) error associated with the corresponding forecast. The smaller the forecast error, hence MSPE, the better the forecasts.

I use the test proposed by Clark and West (2007) to test the equal MSPE of two competing models. The CW test has been widely used in the literature in the past few years to compare the forecast accuracy of two nested models. In the current paper, the no-change forecast and AR(1) model are nested within the MIDAS models. It is thus appropriate to use the CW test. Note that the popular Diebold-Mariano (DM) or Modified Diebold-Mariano (MDM) tests are not applicable here as they only deal with non-nested models. Specifically, define the MSPE of the first forecast and the adjusted MSPE of the second forecast as in equation (10), then CW test the null hypothesis of equal MSPE by examining whether $(MSPE_1 - (MSPE_2 - adj.))$ is sufficiently positive. The null hypothesis is rejected if the test statistics is greater than +1.282 for a one-sided 0.10 test or +1.645 for a one-sided 0.05 test.

$$MSPE_1 = \frac{1}{N}\sum_{i=1}^{N}(P_t^M - \hat{P}_{1t}^M)^2, \text{ and}$$

(10)

$$MSPE_2 - adj. = \frac{1}{N}\sum_{i=1}^{N}\left(P_t^M - \hat{P}_{2t}^M\right)^2 - \frac{1}{N}\sum_{i=1}^{N}\left(\hat{P}_{1t}^M - \hat{P}_{2t}^M\right)^2.$$

The second indicator of the forecast performance of a model is its success ratio in predicting the directional change of prices. Under the null hypothesis of no directional accuracy, one would expect a model to successfully predict the direction of price changes about 50% of the time. Higher success ratios suggest improved performance of a forecasting model. Following Baumeister, Guérin and Kilian (2014), I use the test developed by Pesaran and Timmermann (2009) to examine the statistical significance of gains in directional accuracy, or success ratio of MIDAS-type forecasts against the alternative forecasting models that do not use exogenous variables (forecasting models (7), the no-change forecast, and (8) ARIMA forecast).

5. Results

Based on the discussion in section three, I consider the following four forecasting models, **i)** the ADL-MIDAS model as in (6), where an exponential Almon function as shown in equation (5) (unrestricted parameters) is used to specify the weighting function, and the lag order of the dependent variable is set to one;[2] **ii)** the equal-weighted MIDAS model, or the ADL-MIDAS model with $\theta_1 = \theta_2 = 0$ in the exponential Almon weighting function as shown in equation (5). As noted earlier, an equal-weighted MIDAS model is equivalent to and ARX model. Similar to the unrestricted MIDAS model, one autoregressive lag is used in the equal-weighted MIDAS model as well; **iii)** the no-change forecast as specified in (7); and **iv)** the ARIMA model as specified in (8), and to match the structure of MIDAS models, I use an AR(1) model in the analysis. The four forecasting models are referred to as U-MIDAS, E-MIDAS, no-change, and AR(1), respectively. To facilitate discussion, predications from U-MIDAS and E-MIDAS models are referred to as MIDAS forecasts, and those from no-change and AR(1) models as benchmark forecasts. When available, we use a rolling window of 120 observations to generate one-month ahead forecasts for each of the four models. Exceptions are the cases when less than 10 years of data are available to estimate the model, and in such case, the maximum sample size is used.

5.1 The Baltic Dry Index (BDI)

Table 2 shows the MSPE and success ratio of MIDAS models using BDI versus benchmark models. The index measures the demand for shipping capacity of industrial products versus the supply of dry bulk carries. Given that the supply of shipping capacity is rather tight and inelastic, the index is very sensitive to the demand of shipping services, which are primary driven by the aggregate global demand of industrial products and raw materials, thus reflecting the global real economic activity (e.g., Klovland 2004). Kilian (2009) further shows that the indicator can capture shifts in the demand for industrial

[2] Preliminary results show that either adding more autoregressive lags or use a different weighting function do not qualitatively change the results. A more detailed discussion on the specification of MIDAS model will be provided in the updated paper.

commodities driven by the global business cycle. The BDI has been used in various studies as a measure of the aggregate global real economic activities, such as McPhail, Du and Muhammad (2012), Bruno, Büyükşahin and Robe (2013), Carter, Rausser and Smith (2013), Etienne, Irwin and Garcia (2014b), and etc.

Since the data for BDI are not available until January 1990, and the first ten years are used to estimate the forecasting model, the one-month ahead out-of-sample forecast is generated for January 2000-August 2014 with a rolling window of ten years. We divide the evaluation period into three sub-periods each consisting of five years, i.e. 2000-2004, 2005-2009, and 2010-2014. As can be seen, the MSPE of both U-MIDAS and E-MIDAS forecasts is higher than the no-change and AR(1) forecasts during 2000-2004 and 2010-2014, but lower during the 2005-2009 episode. The relative MSPE ratios between MIDAS and benchmark models are slightly higher during 2000-2004 than 2010-2014, suggesting an improvement in forecast performance of MIDAS models in the latter period. However, no-change and AR(1) forecasts still outperform both MIDAS forecasts in 2010-2014. The superiority of including daily BDI index in forecasting models during 2005-2009 is somewhat interesting, as this is the period when the BDI experienced its historic highs in volatility (see top plot in figure 2). By capturing the large variations in the index during 2005-2009, the MIDAS models are apparently able to generate superior forecasts relative to the no-change and AR(1) forecasts that do not use the index in the estimation.[3] Despite that, the reduction in MSPE during that period by MIDAS models is small, ranging from 7% to 20%.

The second panel of table 2 shows the success ratios of MIDAS and benchmark forecasts when predicting the next period directional change in corn prices. As can be seen,

[3] The results from the statistical significance test (e.g. the CW test) will be available in an updated version of the paper. Similarly, results from the PT test for success ratio comparisons will be discussed in a later version.

with the exception of no-change forecast in 2010-2014, the success ratios for all other forecasts are higher than 50% during all sub-evaluation periods, which is theoretically the success rate when there is no directional accuracy. However, with the only exception of U-MIDAS forecasts in 2005-2009, success ratios have decreased from the first sub-period to the last sub-period for all four forecasts, suggesting an increasing difficulty in predicting the directional changes in corn prices. It appears that with only one exception (E-MIDAS vs. AR(1)), MIDAS models in general perform no worse than benchmark models when predicating directional changes in corn prices. However, the improvements made by MIDAS model using BDI information is minimal, with the maximum difference in success ratios between MIDAS and benchmark forecasts being 0.07 (2010-2014, U-MIDAS vs. no-change), or about 4 months when the U-MIDAS forecast made correct directional predictions and the no-change forecast did not. Finally, it appears that the relative performance of U-MIDAS over no-change forecasts have slightly increased over time.

5.2 Trade-Weighted Exchange Rate of US Dollars against Major Currencies

The forecast evaluation results for MIDAS models using US exchange rates are shown in table 3. Since the US is a major corn exporter, a weak US dollar is likely to increase exports and reduce the amount of corn available for domestic consumption, contributing to the corn price fluctuations in the US. Abbott, Hurt and Tyner (2008) show that between 2002 and 2007, the trade-weighted US dollar depreciated 22%, while the value of agricultural exports increased 54%, with grain and oilseed exports increasing even more at 63%. They consider the depreciation of the US dollar as one of the primary driving factors behind the 2008 commodity price spike. Other studies find that the falling US dollar played a more minor role. Mitchell (2008), for example, attributes about 20% of the food price increase from January 2002 to February 2008 to dollar weakness. Gilbert (2010a) argues that commodity prices exhibit excess sensitivity to exchange rate movements due to either (1) the business cycle component within exchange rates and commodity prices not captured by other demand-side variables, or (2) the causality when constructing exchange rate indexes that run from commodity prices to exchange rate that includes commodity currencies. It is therefore interesting to test whether exchange rates contain predicative component of future corn price movements.

The exchange rate data are available since January 1973. We use the first seven years as the base estimating sample, and generate the one-month ahead forecast for January 1980. A recursive sample is used in the following estimation and forecasts until a ten-year sample size is reached (December 1982), after which a rolling window is used in the analysis. As can be seen, in the early forecasting cycle, the benchmark models perform no worse or better than MIDAS forecasts. However, MIDAS models perform significantly better than an AR(1) forecast in 1995-1999, and slightly better in 2005-2009 and 2010-2014. It is only during 2010-2014 that MIDAS models perform better than both the no-change and AR(1) forecasts. With the only exception of 2010-2014, the no-change forecasts performs consistently better than both U-MIDAS and E-MIDAS forecasts.

A comparison of success ratios between MIDAS and benchmark forecasts is shown in the second panel of table 2. Results of success ratios appear to be slightly more favorable for MIDAS forecasts compared to those from the MSPE comparisons. Except for the no-change forecast in 2010-2014, all other forecasts have a directional accuracy above 50% during all sub-periods. The U-MIDAS model appears to perform consistently no worse or better than the no-change forecast, whereas E-MIDAS model has a lower directional accuracy for three out of the seven sub-periods relative to the AR(1) forecast, two of which occurred during the latter part of the sample. With the exception of 2005-2009, the AR(1) model performs at least as well as the forecasts generated by a U-MIDAS model. A similar conclusion may be drawn when comparing E-MIDAS and AR(1) forecasts (last column). Regardless, it appears that the difference of success ratios between MIDAS and benchmark forecasts is rather small, ranging from -1% to +1%. This suggests that it remains hard to beat the no-change and AR(1) forecasts by incorporating higher-frequency exchange rate data into the statistical modeling.

5.3 3-Month US Treasury Bill Interest Rate

A high real interest rate is often associated with depressed real commodity prices (Frankel 1986). Baffes and Haniotis (2010) argue that the recent low interest rate occurred in many countries have resulted in excess liquidity, contributing significantly to the 2008 commodity price boom. The role of interest rate has been also emphasized in a number of recent studies, including Frankel (2006), Calvo (2008), and etc.

Table 4 shows the forecast evaluation results of MIDAS models using daily interest rate data. The forecast evaluation period starts from January 1970, and ends in August 2014, and are chronically divided into nine sub-periods of five years. As can be seen, the MSPEs (panel 1) for the no-change forecast are lower than those of the MIDAS forecasts with the only exception of 1985-1989. The MIDAS models outperforms the AR(1) forecasts in three out of seven sub-periods, i.e. 1970-1974, 1985-1989, and 1995-1999. Benchmark models perform consistently no worse or better than both U-MIADS and E-MIDAS models from 2000 to 2014, the period in which corn prices reached historical highs and experienced record-volatility. The largest improvements in MSPEs using MIDAS forecasts occurred in 1995-1999, when the no-change and AR(1) forecasts underperform by 25%. In other cases, the improvements in MSPEs using MIDAS forecasts range from -21% to +3%.

Panel 2 of table 4 shows the success rates of various models in predicting directional corn price changes. It appears that with the exception of the no-change forecast in 2010-2014, all forecasts have a success rate higher than 0.5, the ratio considered to be of no directional accuracy. For all four forecasts, the highest success rate is achieved in 1975-1979, ranging from 0.681 (no-change) to 0.736 (U-MIDAS). The lowest success rate occurred in 2010-2014, ranging from 0.491 (no-change) to 0.544 (AR(1)). It also appears that no apparent pattern exists in the forecast success ratios from periods to periods, suggesting that even with the recent commodity markets financialization, the predictive component embedded in high-frequency interest rate data has not changed much over time when forecasting corn prices. Across forecasting models, it appears that with the only exception of 2010-2014 (U-MIDAS vs. AR(1) and E-MIDAS vs. AR(1)), MIDAS model appear to have a similar, or slightly higher success rate in predicting directional changes than benchmark forecasts. Regardless, the differences are all rather small.

5.4 Nearby WTI Crude Oil Futures Contract Settlement Prices

Oil prices may directly affect corn prices in two ways. The first and traditional channel is the impact of large fluctuations in crude oil prices on the price of fertilizers and transportation costs, which constitute a substantial proportion of crop production costs. The second and more recent channel is due to the rise in ethanol production during the last decade, which has forged links between corn and crude oil prices through demand linkages (e.g., Mallory, Irwin and Hayes 2012). The estimated impact of the increased demand for biofuels on corn prices range from 30% in real terms by Rosegrant, Zhu, Msangi and Sulser (2008) to 70% by Lipsky (2008). In addition, considerable volatility in the crude oil market has been transmitted to the corn market (Trujillo-Barrera, Mallory and Garcia 2012). Indeed, as argued by Wright (2011), demand for corn from ethanol production is the largest exogenous shock on corn prices in recent years.

Table 5 presents the MSPE and success ratios of MIDAS and benchmark forecasts during various sub-periods. One-month ahead forecasts are generated for January 1990-August 2014, which is also the forecast evaluation period. Surprisingly, unlike other financial indicators, it appears that E-MIDAS forecasts of crude oil prices performs significantly worse than the no-change and AR(1) forecasts. The MSPEs of E-MIDAS model are over 250% higher than the no-change forecast in 1995-1999 and 2000-2004, and about 150% higher than the no-change forecast in 2005-2009 and 2010-2014. A rather similar conclusion may be drawn when comparing the E-MIDAS and AR(1) models, though the magnitudes are slightly smaller. The U-MIDAS model performs significantly better than the E-MIADS model, and it outperforms the no-change forecast during 2005-2009, and the AR(1) forecast in 1995-1999 and 2005-2009 by at least 5%. It is apparent that in most cases, incorporating daily crude oil prices in the statistical model produce forecasts that are significantly inferior to both no-change and AR(1) forecasts. Given that crude oil markets are traditionally highly linked to corn markets, the disappointing performance of MIDAS models using crude oil prices is somewhat surprising.

Panel 2 of table 5 shows directional accuracies of MIDAS and benchmark forecasts. As can be seen, MIDAS models all have a success ratio above 50%. It appears that with the exception of 2010-2014, the no-change and AR(1) forecasts have a much higher directional accuracy than the E-MIDAS forecasts. However, the U-MIDAS forecasts perform better than the no-change forecast except in 1990-1994, and the AR(1) forecast except in 1990-1994 and 2010-2014. Regardless, the differences in these success ratios are all rather small.

5.5 The Standard and Poor's 500 (S&P 500) Market Index

Finally, forecast evaluation results of MIDAS model using S&P 500 market index are presented in table 6. The forecast evaluation period starts in January 1970 and ends in August 2014. An overall examination of panel 1 of table 6 suggests that with a few exceptions, benchmark forecasts perform at least as well as MIDAS forecasts. One exception is the period of 1995-1999, when the MSPEs of U-MIDAS and E-MIDAS forecasts are about 25% less than that of the AR(1) forecasts. In the other two cases (2000-2004, E-MIDAS vs. no-change and AR(1); and 2005-2009, E-MIDAS vs. AR(1)), while MIDAS forecasts have a lower MSPE, the differences are very small. By contrast, the no-change forecast outperforms U-MIDAS model by 36% and E-MIDAS model by 29% in 1970-1974. In addition, there is no evidence that the forecast performance of MIDAS models has improved over time, given that the relative ratios of MSPES between MIDAS and benchmark forecasts have no obvious trend.

A comparison of success ratios between MIDAS and benchmark forecasts are presented in panel 2. Again, all four forecasts have a directional accuracy over 50% during most of the sub-periods. The highest directional accuracy occurred in 1975-1979 and 1995-1999, when prices were rather volatile. It appears that MIDAS forecasts in general have a same or slightly higher success rate in predicting directional changes of corn prices relative to benchmark forecasts. However, the differences are rather small, often ranging from one to two additional months that MIDAS forecasts successfully predicted the directional change in prices compared to the no-change or AR(1) forecasts. There is also no evidence that the relative forecasting performance in terms of directional accuracy between MIDAS and benchmark models has improved over time.

6. Conclusions

In this paper, I use the Mixed-data sampling (MIDAS) regression model of Ghysels, Santa-Clara and Valkanov (2004, 2006) to generate monthly corn price forecasts by incorporating daily financial information in the analysis. The performance of MIDAS forecasts is compared with both no-change and autoregressive model forecasts using mean-squared prediction errors and the success ratio in predicting directional changes. The underlying hypothesis is that with the financialization of commodity markets brought by commodity index traders, high-frequency financial data should help to forecast commodity prices. Five high-frequency data series are considered, including the Baltic Dry Index (BDI), the trade-weighted US dollar index against major currencies, the Standard and Poor's (S&P) 500 market index, the 3-month US treasury bill interest rate, and the nearby crude oil futures contract settlement prices. Overall, I find that with only a few exceptions, the no-change and AR(1) forecasts outperform the MIDAS forecasts in that the former generally produces a lower MSPE. While some improvements may be made with the MIDAS forecasts in terms of directional accuracy, the differences between MIDAS and benchmark forecasts are rather small, casting doubt on the usefulness of incorporating higher-frequency financial data in the forecasting model.

Given the enormous amount of money index traders have added to commodity futures markets, it is somewhat surprising to see that financial data contain little predictive information of future corn price movements, and that random walk and autoregressive model forecasts generally produce lower MSPEs than those more complicated forecasts using high-frequency data. In some ways, this may be an indication that cash corn markets in the US are highly efficient, in that past prices reflects most of the information contained in financial markets, and that using forecasts purely based on past data can generate satisfactory forecasts. Despite that, it remains puzzling that MIDAS forecasts generate a much higher MSPE than the no-change and AR(1) forecasts. If the financialization of commodity markets has indeed created a structural change in the commodity markets, and that commodity prices are now jointly determined by financial factors and its own fundamentals (e.g., Tang and Xiong 2012), then clearly some improvements should be made when incorporating financial data in the forecasting model. Results of this paper clearly provide little evidence to support this hypothesis.

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Tables and Figures

Table 1. Details of Data Used in the Paper

Data Series	**Source**	**Frequency**	**Sample Size**	**Adjusted Sample Size**
Average Corn prices Received by Farmers in the US	USDA NASS Agricultural Prices	Monthly	01/1960-08/2014	01/1960-08/2014
Baltic Dry Index (BDI)	Bloomberg	Daily	01/1990-08/2014	01/1990-08/2014
Trade-Weighted US Dollar Index against Major Currencies	Federal Reserve Bank of St. Louis	Daily	01/1973-08/2014	01/1973-08/2014
The Standard and Poor 500 (S&P 500) Market Index	Yahoo! Finance	Daily	01/1950-08/2014	*01/1960-08/2014*
3-Month US Treasury Bill Interest Rate	Federal Reserve Bank of St. Louis	Daily	01/1954-08/2014	*01/1960-08/2014*
Nearby WTI Crude Oil Futures Settlement Prices	NYMEX	Daily	04/1983-08/2014	04/1983-08/2014

Table 2. U-MIDAS and E-MIDAS Forecasts with BDI Index versus No-change and AR(1) Forecasts

Panel 1. MSPE Comparisons

Periods	U-MIDAS	E-MIDAS	No-change	AR(1)	U-MIDAS vs. No-change	U-MIDAS vs. AR(1)	E-MIDAS vs. No-change	E-MIADS vs. AR(1)
2000-2004	0.014	0.012	0.011	0.011	118%	120%	108%	110%
2005-2009	0.041	0.038	0.044	0.049	93%	84%	87%	79%
2010-2014	0.124	0.125	0.113	0.117	109%	106%	110%	106%

Panel 2. Success Rate Comparisons

Periods	U-MIDAS	E-MIDAS	No-change	AR(1)	U-MIDAS vs. No-change	U-MIDAS vs. AR(1)	E-MIDAS vs. No-change	E-MIADS vs. AR(1)
2000-2004	0.638	0.621	0.621	0.638	103%	100%	100%	97%
2005-2009	0.650	0.617	0.600	0.617	108%	105%	103%	100%
2010-2014	0.561	0.544	0.491	0.544	114%	103%	111%	100%

Notes: the last four colums in panel 1 refers to the MSPE ratios of U-MIDAS or E-MIDAS models against the no-change and AR(1) models. A ratio over 100% indicates that the U-MIDAS or E-MIDAS model is inferiror to the no-change or AR(1) model. The last four colums in panel 2 refers to the success rate ratios of U-MIDAS or E-MIDAS models against the no-change and AR(1) model. A ratio over 100% indicates that the U-MIDAS or E-MIDAS forecast is superior to the no-change or AR(1) forecast. In the MIDAS estimation, daily BDI data are used.

U-MIDAS: $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M + \beta \sum_{k=1}^{20} B(k; \boldsymbol{\theta}) L^k X_t^D.$

E-MIDAS: $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M + \beta \sum_{k=1}^{20} \frac{1}{20} L^k X_t^D.$

No-change: $\hat{P}_{t+1}^{M} = P_t^M.$

AR(1): $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M.$

Table 3. U-MIDAS and E-MIDAS Forecasts with Exchange Rate versus No-change and AR(1) Forecasts

Panel 1. MSPE Comparisons

Periods	U-MIDAS	E-MIDAS	No-change	AR(1)	U-MIDAS vs. No-change	U-MIDAS vs. AR(1)	E-MIDAS vs. No-change	E-MIADS vs. AR(1)
1980-1984	0.016	0.016	0.016	0.016	103%	103%	104%	104%
1985-1989	0.014	0.014	0.014	0.014	100%	100%	101%	101%
1990-1994	0.011	0.011	0.011	0.011	101%	105%	100%	103%
1995-1999	0.031	0.032	0.030	0.043	103%	72%	105%	73%
2000-2004	0.013	0.012	0.011	0.011	110%	111%	108%	110%
2005-2009	0.047	0.046	0.044	0.049	105%	96%	105%	95%
2010-2014	0.113	0.111	0.113	0.117	99%	96%	98%	94%

Panel 2. Success Rate Comparisons

Periods	U-MIDAS	E-MIDAS	No-change	AR(1)	U-MIDAS vs. No-change	U-MIDAS vs. AR(1)	E-MIDAS vs. No-change	E-MIADS vs. AR(1)
1980-1984	0.661	0.678	0.633	0.683	104%	97%	107%	99%
1985-1989	0.617	0.617	0.617	0.617	100%	100%	100%	100%
1990-1994	0.593	0.593	0.593	0.593	100%	100%	100%	100%
1995-1999	0.667	0.700	0.650	0.683	103%	98%	108%	102%
2000-2004	0.638	0.655	0.621	0.638	103%	100%	106%	103%
2005-2009	0.633	0.583	0.600	0.617	106%	103%	97%	95%
2010-2014	0.509	0.526	0.491	0.544	104%	94%	107%	97%

Notes: the last four colums in panel 1 refers to the MSPE ratios of U-MIDAS or E-MIDAS models against the no-change and AR(1) models. A ratio over 100% indicates that the U-MIDAS or E-MIDAS model is inferiror to the no-change or AR(1) model. The last four colums in panel 2 refers to the success rate ratios of U-MIDAS or E-MIDAS models against the no-change and AR(1) model. A ratio over 100% indicates that the U-MIDAS or E-MIDAS forecast is superior to the no-change or AR(1) forecast. In the MIDAS estimation, the daily exchange rate data are used.

U-MIDAS: $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M + \beta \sum_{k=1}^{20} B(k;\boldsymbol{\theta}) L^k X_t^D.$

E-MIDAS: $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M + \beta \sum_{k=1}^{20} \frac{1}{20} L^k X_t^D.$

No-change: $\hat{P}_{t+1}^{M} = P_t^M.$

AR(1): $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M.$

Table 4. U-MIDAS and E-MIDAS Forecasts with Interest Rate versus No-change and AR(1) Forecasts

Panel 1. MSPE Comparisons

Periods	U-MIDAS	E-MIDAS	No-change	AR(1)	U-MIDAS vs. No-change	U-MIDAS vs. AR(1)	E-MIDAS vs. No-change	E-MIADS vs. AR(1)
1970-1974	0.034	0.034	0.028	0.036	120%	94%	121%	95%
1975-1979	0.018	0.018	0.017	0.018	107%	101%	108%	101%
1980-1984	0.018	0.017	0.016	0.016	114%	114%	110%	110%
1985-1989	0.014	0.014	0.014	0.014	99%	99%	98%	97%
1990-1994	0.011	0.011	0.011	0.011	101%	104%	103%	106%
1995-1999	0.033	0.033	0.030	0.043	107%	75%	108%	75%
2000-2004	0.011	0.011	0.011	0.011	101%	102%	100%	102%
2005-2009	0.049	0.049	0.044	0.049	110%	100%	110%	101%
2010-2014	0.119	0.119	0.113	0.117	105%	101%	105%	101%

Panel 2. Success Rate Comparisons

Periods	U-MIDAS	E-MIDAS	No-change	AR(1)	U-MIDAS vs. No-change	U-MIDAS vs. AR(1)	E-MIDAS vs. No-change	E-MIADS vs. AR(1)
1970-1974	0.596	0.596	0.579	0.596	103%	100%	103%	100%
1975-1979	0.736	0.722	0.681	0.694	108%	106%	106%	104%
1980-1984	0.683	0.683	0.633	0.683	108%	100%	108%	100%
1985-1989	0.617	0.617	0.617	0.617	100%	100%	100%	100%
1990-1994	0.610	0.610	0.593	0.593	103%	103%	103%	103%
1995-1999	0.683	0.683	0.650	0.683	105%	100%	105%	100%
2000-2004	0.638	0.638	0.621	0.638	103%	100%	103%	100%
2005-2009	0.633	0.617	0.600	0.617	106%	103%	103%	100%
2010-2014	0.526	0.526	0.491	0.544	107%	97%	107%	97%

Notes: the last four colums in panel 1 refers to the MSPE ratios of U-MIDAS or E-MIDAS models against the no-change and AR(1) models. A ratio over 100% indicates that the U-MIDAS or E-MIDAS model is inferiror to the no-change or AR(1) model. The last four colums in panel 2 refers to the success rate ratios of U-MIDAS or E-MIDAS models against the no-change and AR(1) model. A ratio over 100% indicates that the U-MIDAS or E-MIDAS forecast is superior to the no-change or AR(1) forecast. In the MIDAS estimation, the daily intereate data are used.

U-MIDAS: $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M + \beta \sum_{k=1}^{20} B(k;\boldsymbol{\theta}) L^k X_t^D.$

E-MIDAS: $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M + \beta \sum_{k=1}^{20} \frac{1}{20} L^k X_t^D.$

No-change: $\hat{P}_{t+1}^{M} = P_t^M.$

AR(1): $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M.$

Table 5. U-MIDAS and E-MIDAS Forecasts with Crude Oil Prices versus No-change and AR(1) Forecasts

Panel 1. MSPE Comparisons

Periods	**U-MIDAS**	**E-MIDAS**	**No-change**	**AR(1)**	**U-MIDAS vs. No-change**	**U-MIDAS vs. AR(1)**	**E-MIDAS vs. No-change**	**E-MIDAS vs. AR(1)**
1990-1994	0.011	0.018	0.011	0.011	102%	106%	163%	168%
1995-1999	0.033	0.113	0.030	0.043	108%	75%	372%	260%
2000-2004	0.012	0.040	0.011	0.011	105%	106%	351%	357%
2005-2009	0.042	0.107	0.044	0.049	95%	86%	242%	220%
2010-2014	0.121	0.310	0.113	0.117	107%	103%	273%	264%

Panel 2. Success Ratio Comparisons

Periods	**U-MIDAS**	**E-MIDAS**	**No-change**	**AR(1)**	**U-MIDAS vs. No-change**	**U-MIDAS vs. AR(1)**	**E-MIDAS vs. No-change**	**E-MIDAS vs. AR(1)**
1990-1994	0.569	0.517	0.593	0.593	96%	96%	87%	87%
1995-1999	0.717	0.617	0.650	0.683	110%	105%	95%	90%
2000-2004	0.638	0.534	0.621	0.638	103%	100%	86%	84%
2005-2009	0.650	0.550	0.600	0.617	108%	105%	92%	89%
2010-2014	0.491	0.579	0.491	0.544	100%	90%	118%	106%

Notes: the last four colums in panel 1 refers to the MSPE ratios of U-MIDAS or E-MIDAS models against the no-change and AR(1) models. A ratio over 100% indicates that the U-MIDAS or E-MIDAS model is inferiror to the no-change or AR(1) model. The last four colums in panel 2 refers to the success rate ratios of U-MIDAS or E-MIDAS models against the no-change and AR(1) model. A ratio over 100% indicates that the U-MIDAS or E-MIDAS forecast is superior to the no-change or AR(1) forecast. In the MIDAS estimation, the daily crude oil futures price data are used.

U-MIDAS: $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M + \beta \sum_{k=1}^{20} B(k;\boldsymbol{\theta}) L^k X_t^D.$

E-MIDAS: $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M + \beta \sum_{k=1}^{20} \frac{1}{20} L^k X_t^D.$

No-change: $\hat{P}_{t+1}^{M} = P_t^M.$

AR(1): $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M.$

Table 6. U-MIDAS and E-MIDAS Forecasts with S&P 500 Market Index versus No-change and AR(1) Forecasts

Panel 1. MSPE Comparisons

Periods	U-MIDAS	E-MIDAS	No-change	AR(1)	U-MIDAS vs. No-change	U-MIDAS vs. AR(1)	E-MIDAS vs. No-change	E-MIADS vs. AR(1)
1970-1974	0.038	0.036	0.028	0.036	136%	107%	129%	101%
1975-1979	0.018	0.018	0.017	0.018	109%	102%	106%	100%
1980-1984	0.017	0.017	0.016	0.016	111%	111%	110%	110%
1985-1989	0.018	0.017	0.014	0.014	125%	125%	117%	116%
1990-1994	0.012	0.011	0.011	0.011	105%	108%	103%	106%
1995-1999	0.034	0.032	0.030	0.043	111%	77%	105%	73%
2000-2004	0.011	0.011	0.011	0.011	100%	101%	98%	99%
2005-2009	0.050	0.047	0.044	0.049	113%	103%	107%	97%
2010-2014	0.132	0.128	0.113	0.117	116%	112%	112%	109%

Panel 2. Success Ratio Comparisons

Periods	U-MIDAS	E-MIDAS	No-change	AR(1)	U-MIDAS vs. No-change	U-MIDAS vs. AR(1)	E-MIDAS vs. No-change	E-MIADS vs. AR(1)
1970-1974	0.561	0.579	0.579	0.596	97%	94%	100%	97%
1975-1979	0.694	0.694	0.681	0.694	102%	100%	102%	100%
1980-1984	0.667	0.667	0.633	0.683	105%	98%	105%	98%
1985-1989	0.600	0.617	0.617	0.617	97%	97%	100%	100%
1990-1994	0.593	0.610	0.593	0.593	100%	100%	103%	103%
1995-1999	0.700	0.683	0.650	0.683	108%	102%	105%	100%
2000-2004	0.655	0.655	0.621	0.638	106%	103%	106%	103%
2005-2009	0.633	0.633	0.600	0.617	106%	103%	106%	103%
2010-2014	0.526	0.561	0.491	0.544	107%	97%	114%	103%

Notes: the last four colums in panel 1 refers to the MSPE ratios of U-MIDAS or E-MIDAS models against the no-change and AR(1) models. A ratio over 100% indicates that the U-MIDAS or E-MIDAS model is inferiror to the no-change or AR(1) model. The last four colums in panel 2 refers to the success rate ratios of U-MIDAS or E-MIDAS models against the no-change and AR(1) model. A ratio over 100% indicates that the U-MIDAS or E-MIDAS forecast is superior to the no-change or AR(1) forecast. In the MIDAS estimation, the daily S&P 500 data are used.

U-MIDAS: $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M + \beta \sum_{k=1}^{20} B(k;\boldsymbol{\theta}) L^k X_t^D.$

E-MIDAS: $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M + \beta \sum_{k=1}^{20} \frac{1}{20} L^k X_t^D.$

No-change: $\hat{P}_{t+1}^{M} = P_t^M.$

AR(1): $\hat{P}_{t+1}^{M} = \alpha + \rho_1 L^1 P_t^M.$

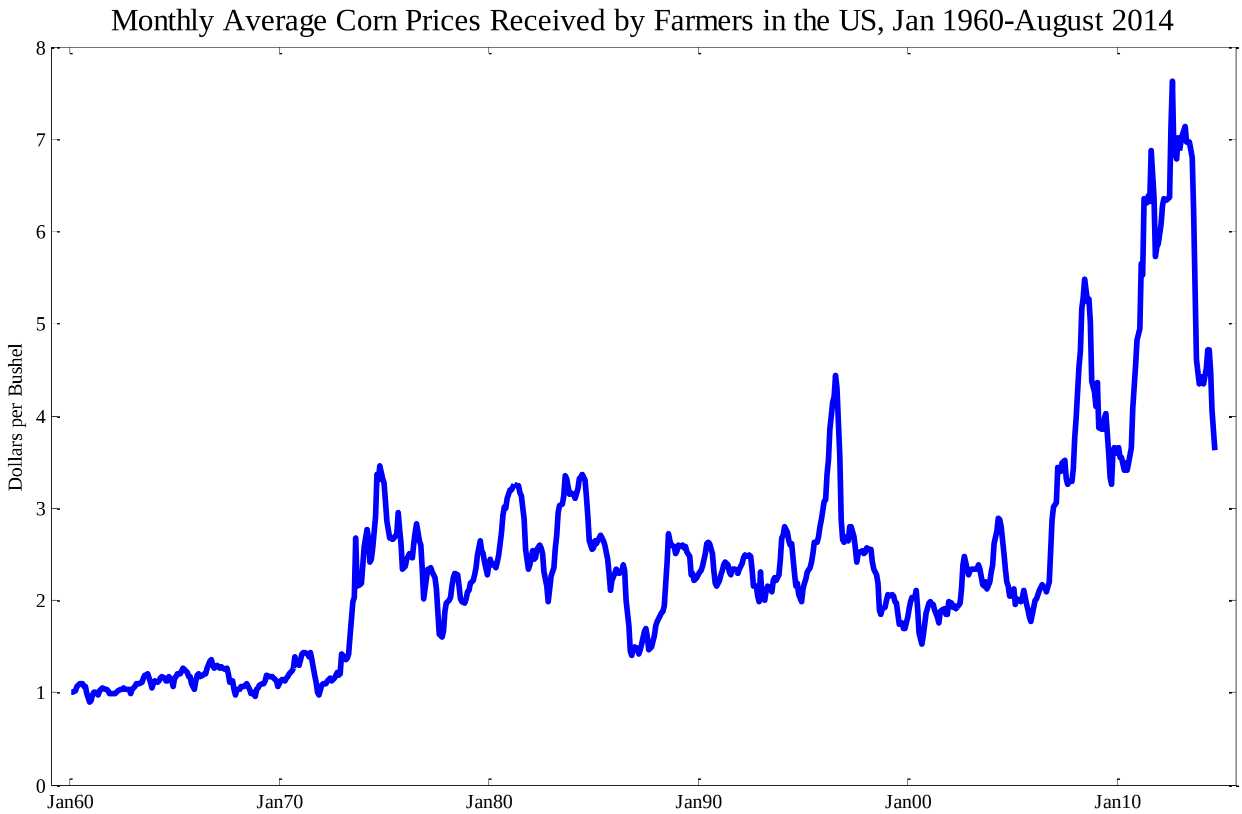

Figure 1. Monthly Average Corn Prices Received by Farmers in the United States, Jan 1960-August 2014

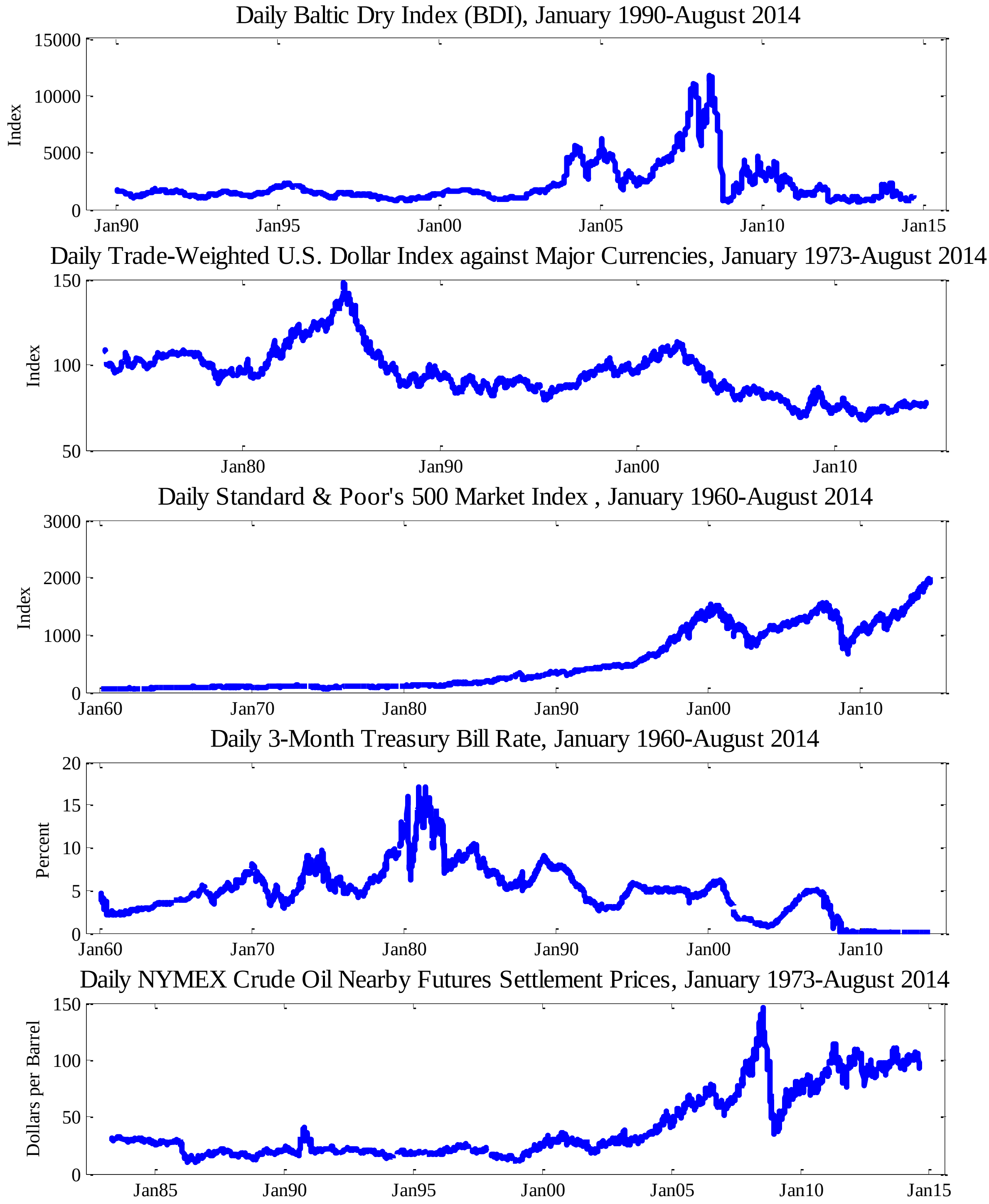

Figure 2. High-Frequency Explanatory Variables Used in the Paper